Simplified Models of Fault Effects on Unitary Air-Conditioning Equipment for use in Building Simulation Tools

David P. Yuill and Mehdi Mehrabi
Architectural Engineering, University of Nebraska-Lincoln, Omaha, USA

Abstract

Building performance models most typically do not account for equipment faults, even though such faults are believed to significantly impact performance. One reason is that fault effects on performance are not very well understood, and can be quite complex to model. To address this situation, the current paper provides a summary of known empirical studies of fault effects on air-cooled unitary equipment. The summary includes three important performance parameters – capacity, efficiency, and sensible heat ratio – for three common fault types. Statistical analyses have been used to provide simplified models that can be programmed into building simulation software.

Introduction

An important element of simulation is that the model accurately represent reality. Often, building simulations do not closely match with measurements, so an important area of study, and step in the simulation process, is model validation (de Wilde, 2014).

A significant potential cause of differences between measured and simulated building energy usage is that the models don't account for faults (Basarkar et al., 2011). Building energy simulation models typically assume that equipment performance, such as efficiency and capacity, is at its specification value, and remains so. However, in reality equipment performance is degraded by installation or degradation faults, so there exists a potential to improve simulation accuracy by correctly accounting for fault effects on performance (Roth et al. 2005, Domanski et al. 2015).

Basarkar et al. (2011) describe methods of imposing several faults in simulation, and recently some models, such as EnergyPlus, have included some fault-enabled equipment models to improve the overall model's realism. The faulted equipment that is modelled tends to be for systems serving large commercial buildings, such as chillers, boilers, hydronic system components, and air distribution system components.

Most buildings, both commercial and residential, use air-cooled unitary systems for cooling (EIA 2016). In the US, about 69% of commercial building space is cooled by packaged units or split systems, and most residential air-conditioners are split systems (EIA 2016). Modelling the effects of faults on these systems can be very difficult. Examples of potential faults that can affect performance include: an improper quantity of refrigerant charge, air-side fouling of the evaporator or condenser, liquid-line restrictions, compressor leakage, non-condensable gas in the refrigerant, and economizer faults.

One difficulty is that the effects of faults as a function of their intensity and operating conditions are not well understood for most fault types. There have been several laboratory studies, described below, in which faults have been imposed upon a particular system, and some studies in which regressions have been applied (e.g. Cho et al. 2014), but it's not clear how well the impacts generalize to other systems. A second problem is that the faults' effects propagate around the cycle, making them difficult to simulate with mechanistic system models.

Despite the difficulties, some fault enabled models have been produced, such as Rice (2005), Shen et al. (2009), and Cheung and Braun (2013a, 2013b), who present a gray-box modelling approach that is capable of modelling the effects of several faults. The latter authors applied their modelling approach to eight unitary air-conditioning systems for which measurement data were available. The models are validated in Yuill et al. (2014) and found to perform well for their intended purpose, which was to test fault detection and diagnosis algorithms.

One drawback of these modelling approaches is that they are very complex. The effort to model a system is significant, and typically requires several specific laboratory measurements to train the model. A related drawback is that the model is computationally expensive; it may take several minutes or hours to converge for a single scenario (operating condition and fault condition). A final problem is summarized in the adage that everybody believes experimental results except the experimenter; while nobody believes modelled results except the modeller.

The objective of the current work is to develop a simpler modelling approach that is sufficiently accurate for the needs of building energy simulation. For this to be possible, it's necessary that the effects of faults on the performance of air-conditioning systems are sufficiently homogeneous that a single model can be implemented to represent a large class of systems (i.e. a separate model is not needed for each unique equipment design). To address the objectives, the authors have gathered available data from all known laboratory tests, and non-dimensionalized them so that they can be compared easily. Since the non-

https://doi.org/10.26868/25222708.2017.378

dimensionalized fault effects have been found to be similar, data reduction and regressions have been conducted to provide simple models that could be implemented in building simulation software.

Methodology

The data used in this study come from several laboratory studies, many of which have a published paper associated with them: Farzad and O'Neal (1993), Breuker and Braun (1998), Gowsami et al. (2001), Davis and D'Albora (2001a, 2001b), Shen (2006), Kim et al. (2006), Kim et al. (2008), SCE (2009, 2012, 2015), Raj and Lal (2010), Kim and Braun (2012), Mowris et al. (2012), Qureshi and Zubair (2014). For 11 of the systems, we obtained data files from the experimenters. For the others we read the data from the papers.

Three faults types that are generally considered in the cited literature to be of most importance (because of their frequency of occurrence and impact) are: charge faults (refrigerant undercharge (UC) or overcharge, (OC)), evaporator fouling (EA), and condenser fouling (CA). These faults are the subject of the current paper.

For each set of data, the independent variable, fault intensity (FI) was normalized using definitions from Yuill and Braun (2013).

Table 1: Definitions of fault intensity

Fault type	Fault Intensity Definition
UC or OC	$FI_{charge} = \frac{m_{actual} - m_{nominal}}{m_{nominal}}$
EA	$FI_{EA} = \frac{\dot{V}_{actual} - \dot{V}_{nominal}}{\dot{V}_{nominal}}$
CA	$FI_{CA} = \frac{\dot{V}_{actual} - \dot{V}_{nominal}}{\dot{V}_{nominal}}$

All of the systems in the data set use single-speed fans. The dominant effect of condenser or evaporator fouling on these systems is to reduce airflow, which reduces heat transfer (Yang et al. 2007). Thus, fouling and airflow reduction are treated interchangeably.

The performance of these systems with a given fault type is a function of four independent variables: outdoor temperature, indoor temperature, indoor humidity, and FI. The normalized performance of a system is typically much more sensitive to FI than operating conditions, so relationships for one set of temperatures can be used across a fairly wide range of temperatures without too much loss of generality. The data presented below for charge faults represent systems operating under a single thermal condition. For the other faults, the data come from a range of conditions, because there aren't sufficient data at any one condition.

The dependent variables of interest – capacity, *Q*, coefficient of performance, *COP*, and sensible heat ratio, *SHR* – are also normalized, with the use of fault impact ratios (FIR), defined in Yuill and Braun (2013). These ratios compare fault performance with unfaulted performance at the same operating conditions. For example, FIR for *COP* is calculated as:

$$FIR_{COP} = \frac{COP_{faulted}}{COP_{unfaulted}}. \qquad (1)$$

Mehrabi and Yuill (2017a) conclude that for refrigerant charge, and condenser fouling faults (Mehrabi and Yuill 2016, 2017b), the fault effects are sufficiently similar across systems that the effects of these faults can be generalized and reasonably modelled with polynomial expressions. An inspection of Figures 1 to 6 shows that this is a reasonable conclusion for the data set in the current paper, which also includes evaporator and condenser fouling effects.

The simplified models that are provided in this paper are three-coefficient polynomial regressions that follow the form:

$$FIR = a_0 + a_1.FI + a_2.FI^2. \qquad (2)$$

To conduct the regressions, the following data reduction method was used. Since the testing was conducted at arbitrary FI values, and with varying numbers of tests carried out for each air conditioning system, it was necessary to preprocess the data so that each piece of equipment and each FI value is equally weighted. The preprocessing followed four steps:

(i) Conduct a second-order least squares regression for each individual system;

(ii) Use the regression to calculate FIR for a fine mesh of discrete FI values;

(iii) Take a mean value at each FI value for the systems included in the analysis;

(iv) Conduct a new least-squares regression through the values calculated in step iii.

A thermostatic expansion valve (TXV) can significantly mitigate the effect of charge variations, and many of the effects of other faults. Therefore, the analyses presented in this paper treat systems with a TXV separately from those with a fixed orifice (FXO) throttling device.

Results and Analysis

The complete set of raw data for variations in refrigerant charge (including both UC and OC) in FXO systems is shown in Figure 1, along with a regression line, shown as a broad transparent line. The regression is the line described in step iv, above (i.e. it is *not* a regression of the data shown in the plots). Each data series represents one system, and is connected by lines to improve readability. The three plots in Figure 1 show, from top to bottom, the fault effects on *Q*, *COP*, and *SHR* across the evaporator. Some of the experimenters didn't provide data that would allow *SHR* to be calculated, so there are fewer series shown in that plot.

The range for each regression is limited to the FI values for which there are at least three systems represented in the experimental data.

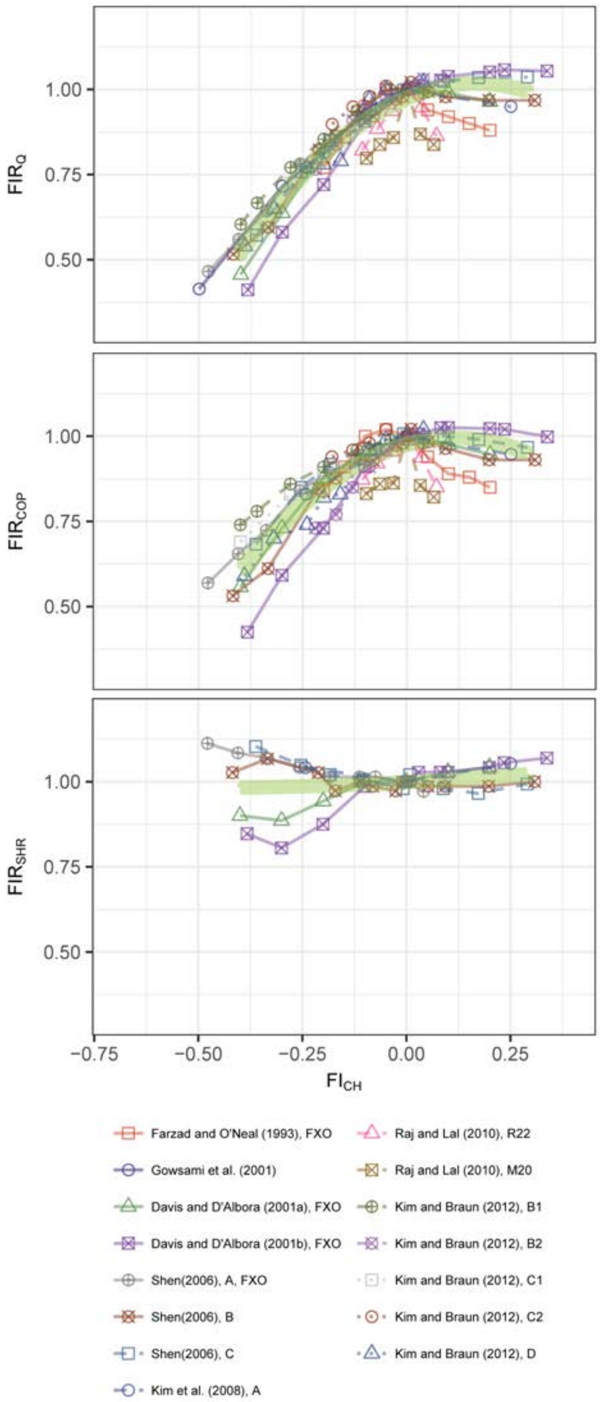

Figure 1: Non-dimensional effects of refrigerant charge on performance of FXO systems at 35/26.7/19.4 °C

The data are fairly tightly clustered, which suggests that using a single regression to represent a broad class of systems is reasonable. An exception is with *SHR*, shown in the lowest plot in Figures 1 and 2. An undercharged system has reduced evaporating pressure, and hence temperature, which will cause it to have a lower air-side coil surface dewpoint temperature in the saturated region of the coil. However, more of the coil will also be superheated, causing it to have a *higher* surface dewpoint temperature. Depending on which of these effects is dominant, the *SHR* can go up or down for UC cases. The resulting regression from the available data shows *SHR* to be insensitive to charge, so it may under- or over-predict *SHR* for any particular system.

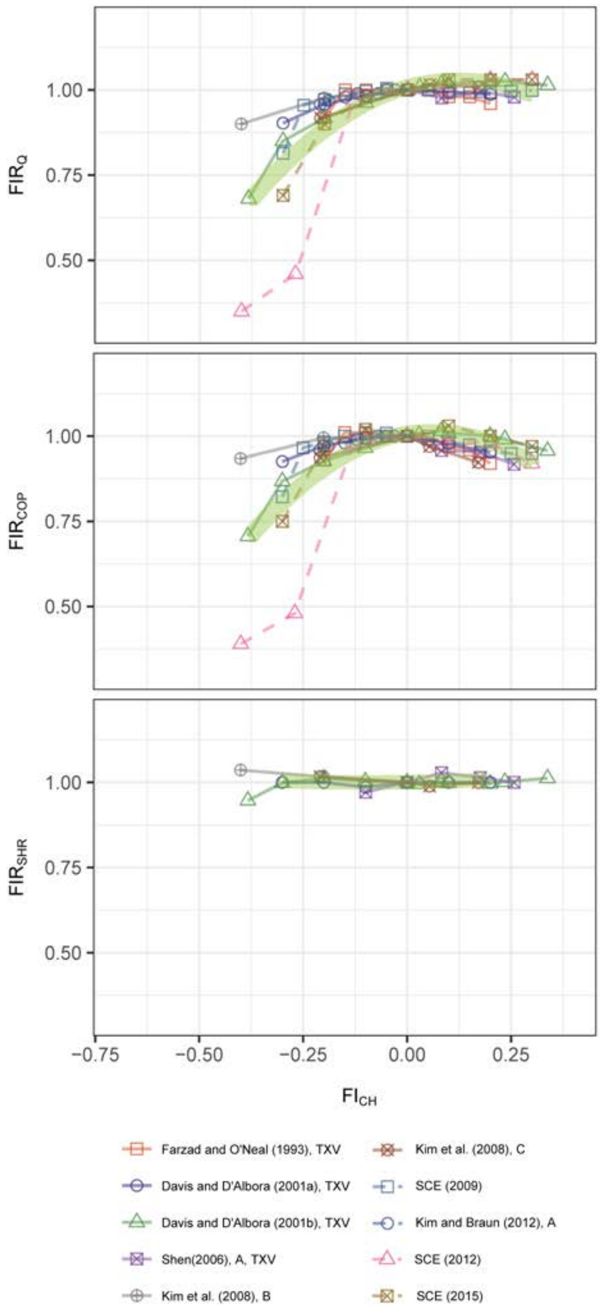

Figure 2: Non-dimensional effects of refrigerant charge on performance of TXV systems

Figure 2 shows that TXV-equipped systems are less sensitive to charge. For UC cases, the TXV may reach its actuation limit, and become a fixed orifice for very low charge levels. The point at which this occurs varies from one system to the next, and hence the divergence for FI < -0.2. One system's performance is quite different from the others' for two UC cases. These data were not included in the analysis because there is evidence that there were some experimental problems for this system. As with FXO systems, the *SHR* is not sensitive to charge.

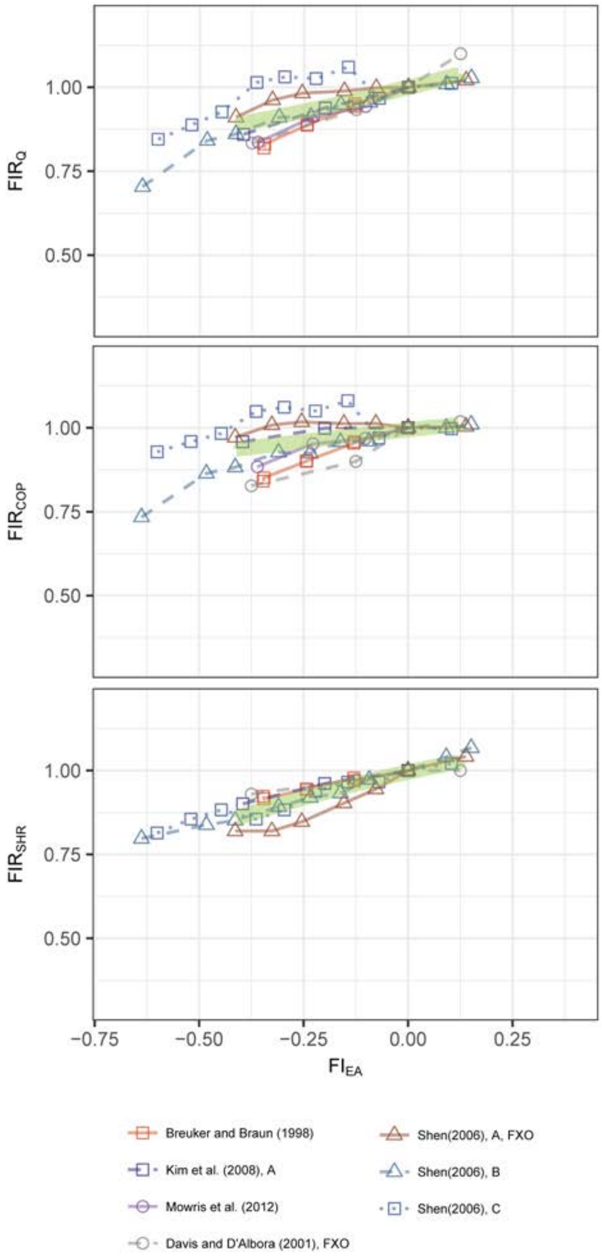

Figure 3: Non-dimensional effects of evaporator airflow on performance of FXO systems

The available data for systems with evaporator airflow faults, shown in Figures 3 and 4, is far sparser than for charge faults. However, the results agree reasonably well, and are not surprising; they agree with expectations based on theory. There is a larger scatter among capacity and efficiency results for FXO systems (Figure 3) than TXV systems (Figure 4). One series in particular, Shen (2006) C, has several data above FIR = 1.0, accounting for much of this scatter. It seems likely that the test at $FI_{EA} = 0.0$ had a problem, which offsets all of the other data because that test defines the normalization of FIR.

The capacity increases with increasing airflow, but efficiency tails off because the increase in fan energy begins to outweigh improved cycle efficiency at higher airflows. *SHR* decreases with airflow because the reduced evaporator temperature means that more latent heat is removed from the air stream.

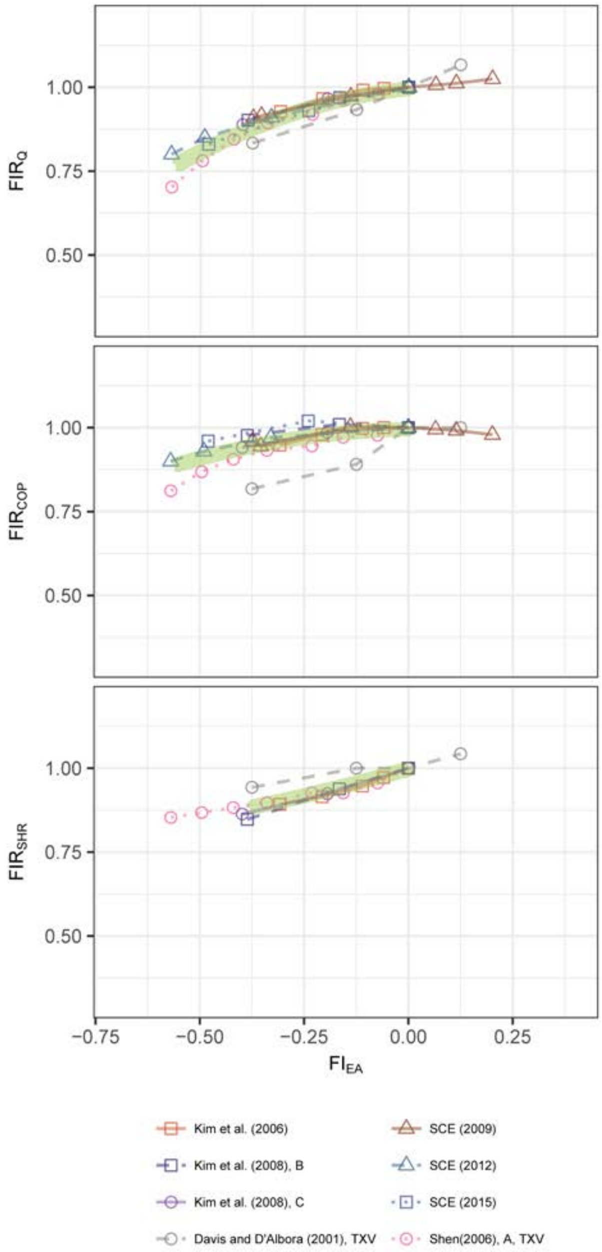

Figure 4: Non-dimensional effects of evaporator airflow on performance of TXV systems

Figures 5 and 6 show that in both FXO and TXV equipped systems, the effects from reducing condenser airflow (to simulate the effect of fouling) are not very dramatic, considering what would reasonably be expected in typical air-side fouling scenarios. Even when airflow is *halved* the capacity is still above 80% of the unfaulted value. *COP* is slightly more sensitive, but for an extreme and unrealistic case with a 90% reduction in condenser airflow, the *COP* is still at 40% of its unfaulted value.

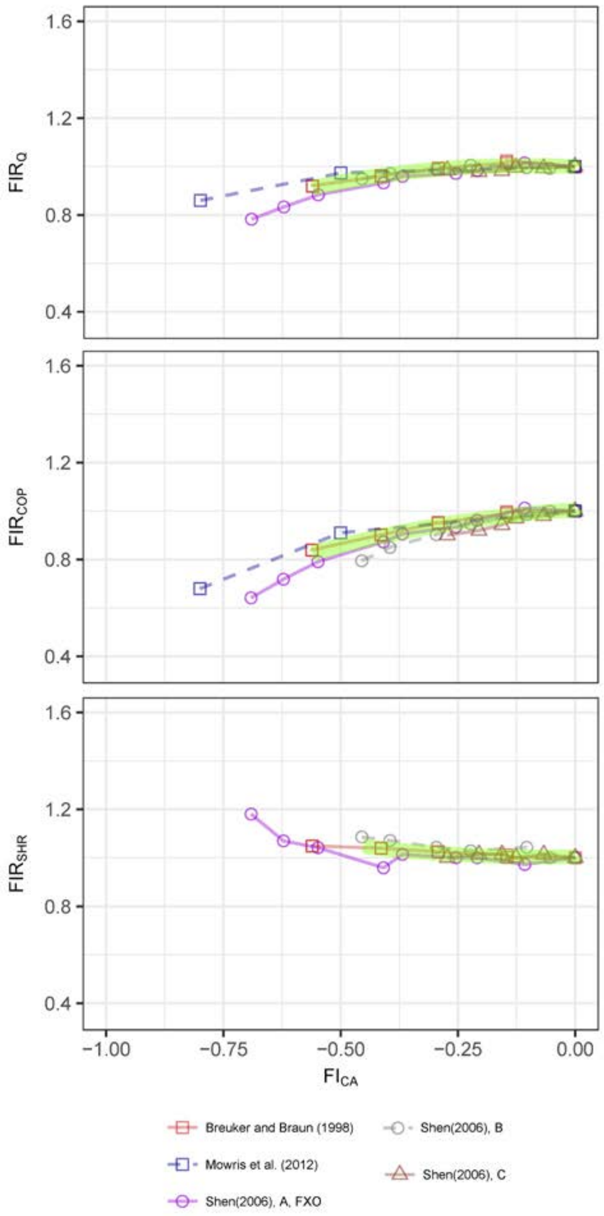

Figure 5: Non-dimensional effects of condenser airflow on performance of FXO systems

This insensitivity doesn't mean that condenser fouling should necessarily be tolerated; the additional head pressure and higher operating temperature for the compressor may decrease its service life.

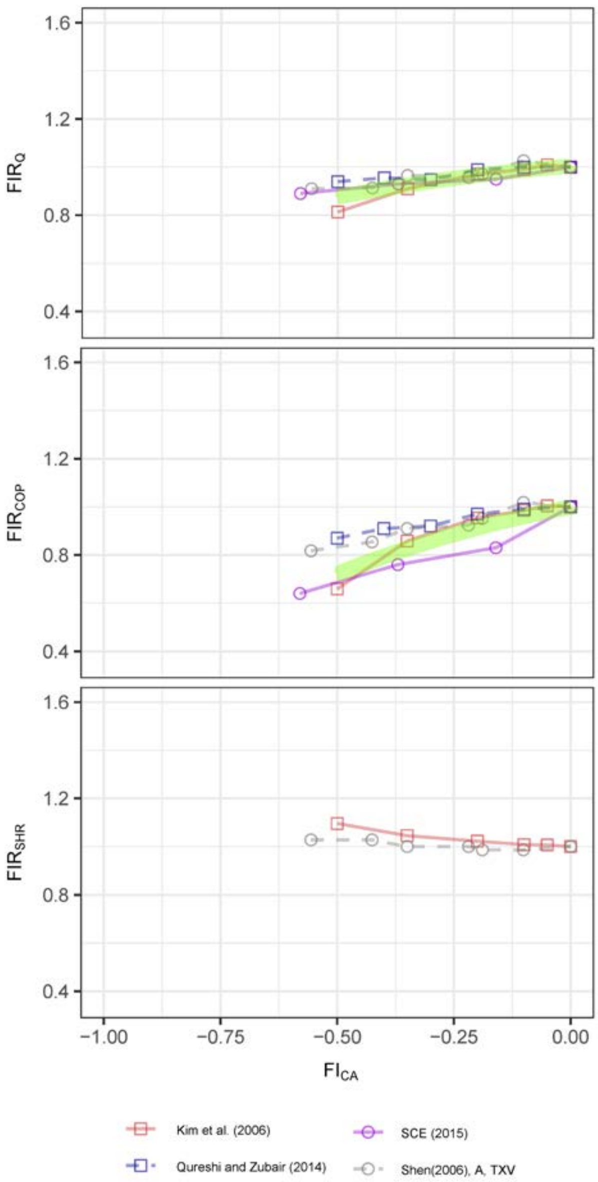

Figure 6: Non-dimensional effects of condenser airflow on performance of TXV systems

Tabular Data

To facilitate usage of these regression in fault-enabled building energy simulations, regression coefficients are provided in Tables 2 and 3, based on Equation (2). The applicable range of fault intensities is provided. The range is based upon the requirement that a minimum of three experimental results must exist at a given FI.

Table 2: Regression results for FXO equipped systems

Normalized Variable	Fault Type	a_0	a_1	a_2	Applicable Range
FIR_Q	CH	0.97728	0.49722	-1.52838	$-0.41 \le FI_{CH} \le 0.29$
	EA	1.00113	0.30858	0.09743	$-0.41 \le FI_{EA} \le 0.12$
	CA	0.99857	-0.10133	-0.44736	$-0.56 \le FI_{CA} \le 0$
FIR_{COP}	CH	0.97807	0.32443	-1.47617	$-0.4 \le FI_{CH} \le 0.29$
	EA	0.99478	0.13133	-0.02258	$-0.41 \le FI_{EA} \le 0.12$
	CA	1.00497	0.11028	-0.36161	$-0.56 \le FI_{CA} \le 0$
FIR_{SHR}	CH	0.99869	0.06327	0.05993	$-0.4 \le FI_{CH} \le 0.29$
	EA	0.99671	0.26567	-0.15955	$-0.41 \le FI_{EA} \le 0.12$
	CA	1.00517	0.04734	0.30132	$-0.45 \le FI_{CA} \le 0$

Table 3: Regression results for TXV equipped systems

Normalized Variable	Fault Type	a_0	a_1	a_2	Applicable Range
FIR_Q	CH	1.01041	0.33156	-1.41075	$-0.38 \le FI_{CH} \le 0.3$
	EA	0.99636	0.12314	-0.49924	$-0.56 \le FI_{EA} \le 0$
	CA	1.00415	0.14358	-0.21954	$-0.50 \le FI_{CA} \le 0$
FIR_{COP}	CH	1.00920	0.17685	-1.60799	$-0.38 \le FI_{CH} \le 0.3$
	EA	0.99534	0.01950	-0.30055	$-0.56 \le FI_{EA} \le 0$
	CA	0.99964	0.34133	-0.41610	$-0.50 \le FI_{CA} \le 0$
FIR_{SHR}	CH	1.00095	0.01795	0.09540	$-0.3 \le FI_{CH} \le 0.19$
	EA	0.99981	0.35765	0.13877	$-0.38 \le FI_{EA} \le 0$

For some applications, it may be more useful to have the expected FIR at a discrete set of FI values. These are provided in tables 4 and 5. In addition, to indicate the expected range of results, the standard deviation is provided. For example, in an FXO system with 20% undercharge (FI_{CH} = -0.2), we see that the capacity will be reduced to 80.7% of its nominal unfaulted value (FIR_Q = 0.807), with a standard deviation of 3.6%.

Table 4: FIR values and standard deviation at discrete FI values FXO equipped systems

Normalized Variable	Fault Type	FI							
		-0.5	-0.4	-0.3	-0.2	-0.1	0	0.1	0.2
FIR_Q	CH	-	0.546 0.050	0.678 0.048	0.807 0.036	0.925 0.033	1	0.989 0.042	0.979 0.068
	EA	-	0.921 0.054	0.914 0.064	0.946 0.048	0.968 0.0274	1	1.030 0.034	-
	CA	0.937 0.037	0.963 0.017	0.982 0.010	0.993 0.012	1.002 0.010	1	-	-
FIR_{COP}	CH	-	0.639 0.084	0.739 0.080	0.847 0.060	0.942 0.033	1	0.972 0.046	0.949 0.065
	EA	-	0.962 0.067	0.945 0.076	0.967 0.061	0.978 0.034	1	1.004 0.008	-
	CA	0.865 0.046	0.890 0.036	0.929 0.022	0.957 0.021	0.990 0.014	1	-	-
FIR_{SHR}	CH	-	1.006 0.095	0.975 0.120	0.985 0.063	1.003 0.012	1	1.008 0.024	1.011 0.036
	EA	-	0.847 0.025	0.901 0.042	0.938 0.032	0.967 0.018	1	-	-
	CA	-	1.027 0.052	1.025 0.019	1.014 0.014	1.006 0.027	1	-	-

Table 5: FIR values and standard deviation at discrete FI values for TXV equipped systems

Normalized Variable	Fault Type	FI							
		-0.5	-0.4	-0.3	-0.2	-0.1	0	0.1	0.2
FIR_Q	CH	-	-	0.772 0.186	0.916 0.080	0.982 0.013	1	1.002 0.018	1.005 0.029
	EA	0.812 0.034	0.868 0.014	0.913 0.023	0.947 0.021	0.975 0.013	1	-	-
	CA	0.877 0.055	0.911 0.029	0.943 0.017	0.961 0.013	0.995 0.029	1	-	-
FIR_{COP}	CH	-	-	0.798 0.182	0.935 0.080	0.991 0.018	1	0.983 0.026	0.967 0.032
	EA	0.913 0.042	0.948 0.034	0.952 0.050	0.973 0.045	0.986 0.031	1	-	-
	CA	0.726 0.094	0.802 0.066	0.863 0.070	0.904 0.076	0.965 0.064	1	-	-
FIR_{SHR}	CH	-	-	1.008 0.016	1.011 0.008	1.002 0.011	1	1.004 0.015	-
	EA	-	-	0.907 0.031	0.934 0.027	0.964 0.021	1	-	-

Discussion

The models presented above are very simple, so they do not impose a significant computational expense nor programming effort. Their simplicity has some trade off with accuracy, but in the context of a typical building energy simulation, the loss of accuracy would typically be within the bounds of uncertainty on the simulation. Therefore, these models are recommended for this purpose.

These models are based on existing data from systems manufactured over the past 30 years. More recently-produced systems typically have higher efficiency, and more significantly, many currently manufactured systems have microchannel heat exchangers, which may affect charge sensitivity and potentially sensitivity to heat exchanger fouling. Thus, the models provided in this paper may not represent performance of more modern systems very well.

These models are not recommended for use in fault detection and diagnosis (FDD). The reason is that they may be thought of as multiple input, single output models. It's not mathematically possible to use them backwards.

For example, if measurements show FIR effects that closely match the models' values for a given fault, it may be that this fault is present, or it may be that some combination of faults is present, or it may be that some other fault that isn't discussed here is present. The resulting erroneous results would likely outweigh the value of any correct results. An evaluation of the performance of several existing FDD approaches by Yuill and Braun (2017) found that most of them give negative value (i.e. erroneous results or oversensitivity cause more cost than benefit), and concludes that one of the reasons is that the algorithms are overly simplified, using the same erroneous approach described above.

Users of these results should also be cautious when drawing conclusions about whether to tolerate a fault or to address it, based on a comparison of energy costs with service costs. Yuill and Braun (2017) also note that a fault's economic impact associated with equipment wear is often more significant than its associated energy costs.

The impacts of faults do not tend to be additive, so superposition of FIR model results is not valid for multiple simultaneous faults. All of the data analysed in this paper had a single fault (or no fault).

One important input that is still not well understood is fault prevalence: the probability of the occurrence of faults by fault type and fault intensity. A combination of fault prevalence with fault impacts would provide a building performance simulation with greater realism.

Conclusions

Simplified data-driven models of the effects of faults on single-speed unitary air-conditioning equipment have been developed using data reduction and regression techniques on a large set of laboratory measurement data. The fault models presented simulate three common faults: refrigerant charge, evaporator fouling, and condenser fouling. The models give non-dimensionalized effects on capacity, *COP* and *SHR*, as a function of fault intensity. The analysis shows that the non-dimensionalized effects of faults on several different systems are sufficiently homogeneous that a single generalized model can be used for typical building energy simulations without increasing the uncertainty of the results significantly. Data reduction techniques are used to generate these generalized models. The model coefficients are presented for adoption into building simulation software. In addition, a set of standard deviation data are provided to enable analysis of uncertainty when deploying these models.

Although the models presented here are deemed appropriate for building simulation, they may not be appropriate for other applications, such as fault detection and diagnosis or maintenance scheduling.

As testing results from modern higher-efficiency systems, and those with microchannel heat exchangers, become available, additional models should be developed to represent these systems and augment the model set provided in this paper.

Nomenclature

CA	condenser fault
CH	charge
COP	coefficient of performance
EA	evaporator fault
FI	fault intensity
FIR	fault impact ratio
FXO	fixed orifice expansion valve
Q	capacity of air conditioner
SHR	sensible heat ratio
TXV	thermostatic expansion valve

References

AHRI Standard 210/240 (2008). *Performance rating of unitary air-conditioning and air-source heat pump equipment*. Air-Conditioning, Heating, and Refrigeration Inst., Arlington, VA, USA.

Basarkar, M., P. Haves, X. Pang, L. Wang, and T. Hong (2011). Modeling and simulation of HVAC faults in EnergyPlus. *Proceedings of Building Simulation 2011*. Sydney, Australia,

Breuker, M.S. and J.E. Braun (1998). Common faults and their impacts for rooftop air conditioners. HVAC&R Research 4(3), 303-318.

Cheung, H. and J.E. Braun (2013a). Simulation of Fault Impacts for Vapor Compression Systems by Inverse Modeling Part I: Component Modeling and Validation. *HVAC&R Research* 19(7), 892-906.

Cheung, H. and J.E. Braun (2013b). Simulation of Fault Impacts for Vapor Compression Systems by Inverse Modeling Part II: System Modeling and Validation, *HVAC&R Research* 19(7), 907-921.

Cho, J.M., J. Heo, W.V. Payne and P.A. Domanski (2014). Normalized performance parameters for a residential heat pump in the cooling mode with single faults imposed. *Applied Thermal Engineering.* 67(2014), 1-15.

Davis, R. and E. D'Albora (2001a). *Influence of the Expansion Device on the Performance of a Residential Split-System Air Conditioner*. Report for Pacific Gas and Electric Company, San Francisco, CA.

Davis, R. and E. D'Albora (2001b). *Influence of expansion device and refrigerant charge on the performance of a residential split-system air conditioner using R-410a refrigerant*. Report for Pacific Gas and Electric Company, San Francisco, CA.

De Wilde, P. (2014). The gap between predicted and measured energy performance of buildings: A framework for investigation. *Automation in Construction*. 41(2014), 40-49.

Domanski, P. A., H. Henderson and W. V. Payne (2015). Effect of heat pump commissioning faults on energy use in a slab-on-grade residential house. *Applied Thermal Engineering 90*, 352-361.

Energy Information Administration (EIA) (2016). 2012 Commercial Buildings Energy Consumption Survey (CBECS). U.S. Dept of Energy. Washington, D.C.

Farzad, M. and D.L. O'Neal (1993). Influence of the expansion valve on air-conditioner system performance characteristics under a range of charging conditions. *ASHRAE Trans.* 99(1), 3-13.

Goswami, D. Y., G. Ek, M. Leung, C. K. Jotshi, S.A. Sherif and F. Colacino (2001). Effect of refrigerant charge on the performance of air conditioning systems. *International Journal of Energy Research* 25(8), 741-750.

Kim, J.H., J.E. Braun, E.A. Groll, and L. Palmer (2008). *Final report on off-design performance of residential heat pumps*. Sponsored by ASHRAE, Atlanta, GA, and Ecotope, Inc., Seattle, WA.

Kim, M., W.V. Payne, P.A. Domanski and C.J.L. Hermes (2006). *Performance of a residential heat pump operating in the cooling mode with single faults imposed*. NISTIR 7350. NIST, Gaithersburg, MD.

Kim, W. and J.E. Braun (2012). Evaluation of the impacts of refrigerant charge on air conditioner and heat pump performance. *International Journal of Refrigeration* 35(7), 1805-1814.

Mehrabi, M. and D.P. Yuill (2016). Normalized effect of condenser fouling and refrigerant charge on performance of vapor compression air conditioning systems. *Proceedings of 16th International Refrigeration and Air Conditioning Conference at Purdue*, West Lafayette, IN.

Mehrabi, M. and D.P. Yuill (2017a). Generalized effects of refrigerant charge on normalized performance variables of air conditioners and heat pumps. *International Journal of Refrigeration*, 76, 367-384.

Mehrabi, M. and D.P. Yuill (2017b). Generalized effects of faults on normalized performance variables of air conditioners and heat pumps. *International Journal of Refrigeration* (In review).

Mowris, R., E. Jones and R. Eshom (2012). Laboratory measurements of HVAC installation and maintenance faults, *ASHRAE Trans* 118(2), 165-172.

Qureshi, B. A. and S. M. Zubair (2014). The impact of fouling on the condenser of a vapor compression refrigeration system: An experimental observation. *International Journal of Refrigeration 38*, 260-266.

Raj, M.H. and D.M. Lal (2009). An experimental analysis of the effect of refrigerant charge level and outdoor condition on a window air conditioner. *Thermal Science* 14(4), 1121-1138.

Rice, C. K. (2005). DOE/ORNL Heat Pump Design Model on the Web, Mark VII Version. from http://web.ornl.gov/~wlj/hpdm/MarkVI.shtml accessed on 12/2016.

Roth, K. W., D. Westphalen, P. Llana, M. Feng, and L. Quartararo (2005). *Energy impact of Commercial Building Controls and Performance Diagnostics: Market Characterization, Energy Impact of Building Faults, and Energy Savings Potential*. Final Report to Department of Energy, CTC-030500202, 413 p. Washington, D.C., USA.

Southern California Edison (SCE) (2009). *HVAC Maintenance*, ETO 08.02-08.09 Report. Rosemead, CA.

Southern California Edison (SCE) (2012). Evaluating the effects of common faults on a residential split system, HT.11SCE.007 Report. Rosemead, CA.

Southern California Edison (SCE) (2015). *Evaluating the effects of common faults on a commercial packaged rooftop unit*, ET13SCE7050 Report. Rosemead, CA.

Shen, B. (2006). *Improvement and validation of unitary air conditioner and heat pump simulation models at off-design conditions*. Doctoral Thesis, Mechanical Eng., Purdue University. West Lafayette, IN.

Shen, B, J.E. Braun, and E.A. Groll (2009). Improved methodologies for simulating unitary air conditioners at off-design conditions. *International Journal of Refrigeration* 32(7), 1837-1849.

Yang, L., J. E. Braun and E. A. Groll (2007). The impact of fouling on the performance of filter–evaporator combinations. *International Journal of Refrigeration*, *30*(3), 489-498.

Yuill, D.P. and J.E. Braun (2013). Evaluating the performance of FDD protocols applied to air-cooled unitary air-conditioning equipment. *HVAC&R Research* 19(7), 882-891.

Yuill, D.P. and J.E. Braun (2017). A figure of merit for overall performance and value of AFDD tools. *International Journal of Refrigeration*, 74, 649-659.

Yuill, D.P., H. Cheung and J.E. Braun (2014). Validation of a Fault-Modeling Equipped Vapor Compression System Model Using a Fault Detection and Diagnostics Evaluation Tool. *International Refrigeration and Air Conditioning Conference*, Paper 2606, July 14-17.